Method in their madness: Explaining how designers think and act through the cognitive co-evolution model

Philip Cash, Northumbria University, UK

Milene Gonçalves, Delft University of Technology (TU Delft), the Netherlands

Kees Dorst, University of Technology Sydney, Australia

Designers often face situations where the only way forward is through the exploration of possibilities. However, there is a critical disconnect between understanding of how designer's think and act in such situations. We address this disconnect by proposing and testing (via protocol analysis) the cognitive co-evolution model. *Our model comprises a new approach to co-evolutionary design theory by explaining both the progression of the process itself and the creation of design outputs via an interplay between metacognitive perceived uncertainty, cognition, and the external world. We thus connect explanations of how designers think with descriptions of how they act. We provide a foundation for connecting to other theories, models, and questions in design research via common links to cognition and metacognition.*

Keywords: co-evolution, design process(es), design cognition, design thinking, creativity

Corresponding author:
Philip Cash
philip.cash@northumbria.ac.uk

Designers often face situations characterised by multiple variables, unknowns, and little stable ground, where the only way forward is through the exploration of possibilities. Understanding how designers overcome such situations and think about exploration is one of the key motivating factors behind design research (Cross, 1982). Central to this is the idea that designers employ abductive processes (e.g., Kroll & Koskela, 2015). Abduction (after Peirce, as quoted by Roozenburg and Eekels 1995) can be defined as a way of "thinking backwards" from (desired) consequences (the VALUE) to causes (the WHAT), when both the WHAT and the HOW (the work principle) are unknown (Dorst, 2015). This thought process is both open-ended and emergent, with designers repeatedly proposing, evaluating, and rejecting possible WHATs (from the solution space) and HOWs (from the problem space), with no single, fixed-end point.

www.elsevier.com/locate/destud
0142-694X *Design Studies* **88** (2023) 101219
https://doi.org/10.1016/j.destud.2023.101219

The outcomes of this process have been described in terms of co-evolution in design (Figure 1-A). Here, the designer navigates the HOW related ‘problem space’ and the WHAT related ‘solution space’, until she or he finds an emergent ‘fit’ between an interpretation of the problem and a potential solution (‘an idea’ in design). Co-evolution was originally adapted from biology as the basis for a computational model of design exploration (Maher & Poon, 1996), but has developed to become a powerful descriptive metaphor for human design work (Crilly, 2021a; Dorst & Cross, 2001). However, the emergent nature of behaviour means that there is a divide between *description*, where behaviour can appear as almost random trial-and-error (Gabora, 2011; Simonton, 2010), and *explanation*, where cognition provides distinct patterns of thinking moving the process forward (Ball & Christensen, 2019). To quote Nigel Cross, quoting from Shakespeare’s Hamlet: ‘Though this be madness, yet there is method in’t’ (Cross, 1996).

This creates a disconnect between foundational explanations (based on designer’s thinking) and descriptions of design (based on emergent problem and solution propositions). Specifically, the current co-evolution model merely describes a principle, the to-ing and fro-ing between the problem and solution space, reflected in the proposition of new HOWs and WHATs. Hence, while they are useful, current co-evolutionary descriptions do not explain how the process happens, when it should happen, and what might indicate a ‘good’ process. And, failing this, again opens the door to mistaking apparent trial-and-error behaviour on the surface and ignoring more structured underlying cognition. We need to close that door by more closely connecting description of what designers do to explanation of how designers think. However, in the context of co-evolution, this must overcome four key challenges.

i) **Scale**: co-evolution flattens multi-scale processes, when used to describe both second-by-second individual work and group work across a whole design project (Crilly & Moroşanu Firth, 2019; Maher & Tang, 2003; Wiltschnig, Christensen, & Ball, 2013). However, behaviour emerges from distinct mechanisms of action at different scales (Gorman, 2014), which need to be distinguished.
ii) **Context**: co-evolution presents problem and solution spaces isolated from context (Maher & Poon, 1996). However, behaviour is situated, with cognition mediating interaction between the internal (e.g., a designer’s wider understanding of the world) and external (e.g., a designer’s representations of WHATs and HOWs) (Cash & Kreye, 2017; Scaife & Rogers, 1996).
iii) **Direction**: co-evolution evokes the idea of computer-like control of the process, with spaces being algorithmically, or a-contextually, evaluated and responded to (Maher & Poon, 1996). However, cognition is complex, being shaped by interplay with behaviour and metacognition (i.e.,

reflecting on and directing one's own thinking) (Cash & Kreye, 2017; Scaife & Rogers, 1996).

iv) **Emergence**: co-evolution is described in a linear and continuous fashion, preventing 'non-linear' progression conceptualisations, where a new problem or solution space is disconnected from prior spaces (Dorst, 2019; Maher & Poon, 1996). However, cognition is rife with 'non-linear' references to memory, prior externalisations, and imagination of the future (Evans, 2008).

In this paper, we aim to take a step toward addressing these challenges by building, and subsequently testing, theory that unifies co-evolutionary description and cognitive explanation. First, we describe the conceptual development and integration of co-evolutionary and cognitive theory to propose the *cognitive co-evolution model*. Second, we test the internal coherence and validity of the proposed model using a protocol analysis approach. Our results strongly support the proposed model and firmly close the door on apparent trial-and-error descriptions of co-evolution. Rather, we explain how designers navigate the complexities and unknowns in their problem situations to arrive at a solution.

1 Unifying description and explanation: developing the cognitive co-evolution model

Before it is possible to tackle the unification of description and explanation, we must first address the challenge of *scale* (Figure 1-B). With this, we refer to the need for a consistent grounding for conceptualisation of co-evolution's basic elements (problem/solution spaces and transitions between them). While co-evolution has been described at a range of scales, each of which could invite their own explanatory lens, we adopt cognition as our basic lens for three main reasons. First, individual cognition, and associated second-by-second behaviour, provide a foundation for explaining human behaviour across scales (Gorman, 2014; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2016). Second, cognitive logic builds on several distinctive relationships — and associated causal explanations — that can be observed and tested (Evans & Stanovich, 2013; Wiltschnig et al., 2013). This multitude of relationships allows description and explanation at this scale to be differentiated from, for example, the whole project scale. Third, cognition forms the implicit or explicit basis for most prior co-evolutionary descriptions building on protocol analysis, as well as for understanding reasoning (including abduction). Thus, focusing on the cognitive scale has the potential to scaffold reunification of description and explanation of co-evolutionary design.

Given this scale, the second step towards connecting co-evolution and cognition is addressing the challenge of *context*. This can be illustrated by a fictional example: Consider interaction designer Sarah. She was briefed by a large children's related products manufacturer to design for the promotion of good sleeping habits in young children. Sarah initially defined a rough problem context (including multiple possible influences on children's sleeping habits) and the value an ideal solution should bring (e.g., providing both children and parents an uninterrupted night of sleep). Drawing on computational logic, current co-evolutionary literature defines problem/solution spaces as state spaces, whose populations comprise the set of possible configurations of the system (Crilly, 2021b; Maher & Poon, 1996). However, in cognitive terms this translates to two related elements.

a) Knowledge about the possible extent of a space and the current population of this (in Sarah's case, her incomplete and fuzzy awareness of current solutions in the market and potential directions she could explore);
b) Understanding and confidence in this knowledge (Sarah is aware that her context understanding is limited and that she needs to involve both parents and children in her design process) (Dienes & Perner, 1999; Evans & Stanovich, 2013).

Therefore, when a human designer focuses on a particular knowledge element, it is always contextualised by their wider body of knowledge and understanding of the world (both implicit and explicit) (Ackerman & Thompson, 2017; Evans & Stanovich, 2013). For example, what Sarah initially considered a possible solution direction (e.g., "*if children are afraid of the dark, we could empower them to not be afraid*") could be considered a problem in the next instance (e.g., "*how do we empower children to not feel afraid of the dark?*"), switching as co-evolution progresses (Crilly, 2021a) (Figure 1-C). Further, this explains how problem/solution spaces are related to a whole ecology of other spaces (such as a business-related space, leading Sarah to wonder "*how do I sell this solution to the client?*"), which might also co-evolve (Crilly & Moroşanu Firth, 2019). Thus, the cognitive separation of knowledge and understanding about this provides a basis for differentiating explanation of computational and human problem/solution spaces, with the latter being conceptualised as: *designer's knowledge about the problem/solution spaces and their populations, relative to their wider understanding*.

The third step towards connecting co-evolution and cognition is addressing the challenge of *direction*. Specifically, co-evolution progresses via descriptions of designers' 'movement' between spaces over time (co-evolutionary transitions). Building on the cognitive relationship between knowledge and understanding outlined above, such transitions can be explained in relation to metacognitive monitoring and control, which refers to how reasoning is directed in relation to understanding of cognitive processing, memory, and experience (Ackerman & Thompson, 2017; Evans & Stanovich, 2013; Schraw & Dennison, 1994). Specifically, metacognitive monitoring refers to the ability to monitor one's thought processes and knowledge (e.g., Sarah is aware that she does not know enough about children's psychology), while metacognitive control refers to the ability to take steps towards controlling one's cognitive processes (e.g., Sarah decides on a strategy to investigate which psychological factors influence children's sleep). In design, this reflective relationship has been characterised in terms of perceived or epistemic uncertainty (Cash & Kreye, 2017; Christensen & Ball, 2018), previously defined as a "*perceived lack of knowledge by an individual, in the form of deficiencies in any stage or activity of the process that can be characterised as not definite, not known, or not reliable*" (Kreye, Goh, Newnes, & Goodwin, 2012). As such, perceived uncertainty offers a human specific explanation for why and how co-evolutionary transitions happen, based on designers' experienced, subjective, and fluctuating feelings of confidence in their knowledge, with respect to the design task and its context (Ball & Christensen, 2019; Cash & Kreye, 2018). Notably, this brings together *memory* of past tasks and wider experience with anticipation and expectations about the future (*imagination*), and links them to *understanding* of the problem at hand (Figure 1-D). For example, Sarah has worked on similar design problems before and has expectations for how many ideas she creates when she is working well, which together informs how she evaluates and directs her current work. Thus, the introduction of metacognitive perceived uncertainty provides a basis for explaining the direction of co-evolutionary processes, which we conceptualise as: *direction of cognition and behaviour based on designer's perceived uncertainty and associated metacognition*.

The final step in connecting co-evolution and cognition is addressing the challenge of *emergence* – and accounting for the distinctive non-linearity found in human design work (Dorst, 2019). Specifically, we build on the idea of emergence in design as described by Dorst (2019, p. 73). Dorst characterises emergence as both the becoming known of something existing (as in finding a solution) and the bringing into being of something new (as in creating a solution). Hence, we need to be able to account for how co-evolutionary processes can lead to the non-linear appearance of insights and solutions. Here, we build on the extensive body of literature showing how cognition is shaped by interactions with memory and external inputs/outputs, including representations created by the designers themselves (Cash & Kreye, 2017; Scaife & Rogers, 1996). These interactions can again be connected to perceived uncertainty, which has not only been linked to accounts of co-evolution (Wiltschnig et al., 2013), but also to all types of design work, ranging from analogising to information processing and representation (Cash & Kreye, 2018; Christensen & Ball, 2016; Scrivener, Ball, & Tseng, 2000). As such, perceived uncertainty serves to relate progression of cognitive co-evolution, to both the internal and external world of the designer (Evans & Stanovich, 2013; Wiltschnig et al., 2013). Specifically, both Maher and Tang (2003) and Cash and Gonçalves (2017) provide evidence to suggest that progression of co-evolution is linked to distinctive interactions with external representations.

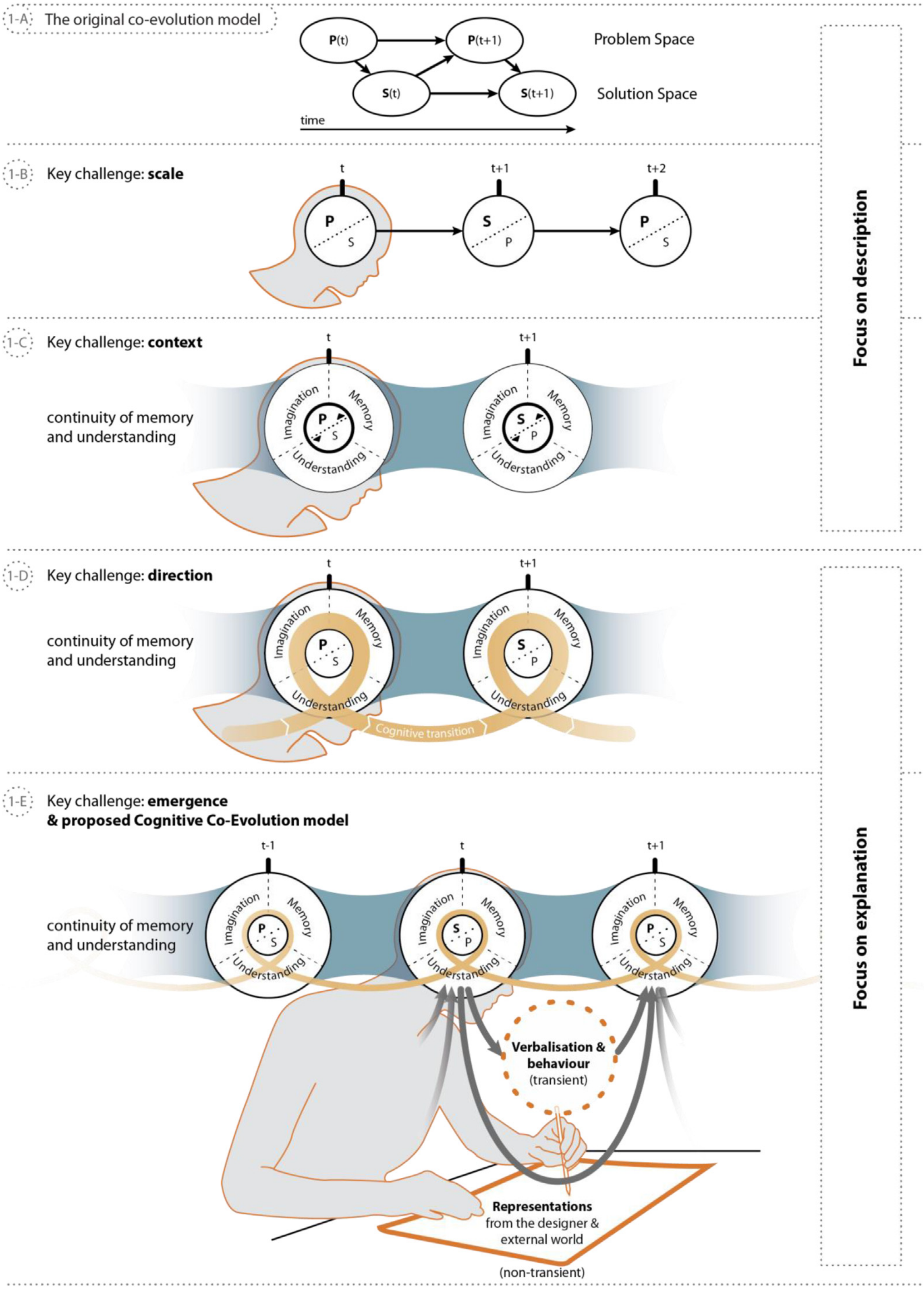


Figure 1 The theory building steps leading to the proposition of the cognitive co-evolution model, as well as definition of the model's basic concepts and relationships as a basis for hypothesis testing

Critically, representations, such as sketches, prototypes, notes or models, facilitate non-linearity by lingering in the context, linking reflection in the moment (e.g., as part of idea creation) with longer-term reflection (e.g., as part of idea evaluation or elaboration) (Goldschmidt, 1990; Gonçalves & Cash, 2021; Martinec, Skec, Perisic, & Storga, 2020). As such, they directly shape how a designer's understanding develops by facilitating an iterative 'back-talk' between external representations, the designer's cognition (including potential imagination of the future (Miller, 2018)), and memory. Coming back to our fictional example, during an ideation session Sarah has examined different perspectives on the problem by iteratively referring to various notes and sketches that she compiled while talking to parents and children earlier in the project. Thus, metacognitive perceived uncertainty provides a basis for explaining non-linearity in human co-evolutionary design work by connecting co-evolution with the inputs and outputs of design work, both in the moment and in the longer-term (Figure 1-E).

Bringing together the conceptualisation in this section, we propose a unification of co-evolutionary description and cognitive explanation in the *cognitive co-evolution model*. Both the theory building steps involved in this conceptualisation and the proposed model are illustrated in Figure 1. The model connects co-evolutionary progression of a designer's knowledge about problem and solution spaces and their populations, to non-linear interaction with their wider understanding (including memory and imagination of the future) and external representations, via metacognitive perceived uncertainty.

2 *Cognitive co-evolution hypotheses*

The cognitive co-evolution model (Figure 1-E) forms the basis for three major hypotheses related to i) the progression of the co-evolutionary process itself; ii) the creation of design outputs and iii) the criticality of the design outputs. These provide a means of assessing internal coherence and validity of the proposed model as illustrated in Figure 2 and detailed below.

First, designers reflect on their work via metacognitive *monitoring* of their own knowledge and cognition (Ackerman & Thompson, 2017; Ball & Christensen, 2019). This means that changes in knowledge should be related to changes in metacognitive perceived uncertainty, as illustrated in Figure 2. In co-evolution, the basic unit for differentiating knowledge progression is the co-evolutionary transition, which has four types: Problem to Problem space (P−P), Problem to Solution space (P−S), Solution to Problem space (S−P), and Solution to Solution space (S−S) (Wiltschnig et al., 2013). While these transitions can always be further decomposed (e.g., with respect to varying cognitive processes during a transition (e.g., Becattini, Cascini, and Rotini (2015)) they form a logical basis for testing this first relationship between knowledge and metacognitive perceived uncertainty. Thus, each co-

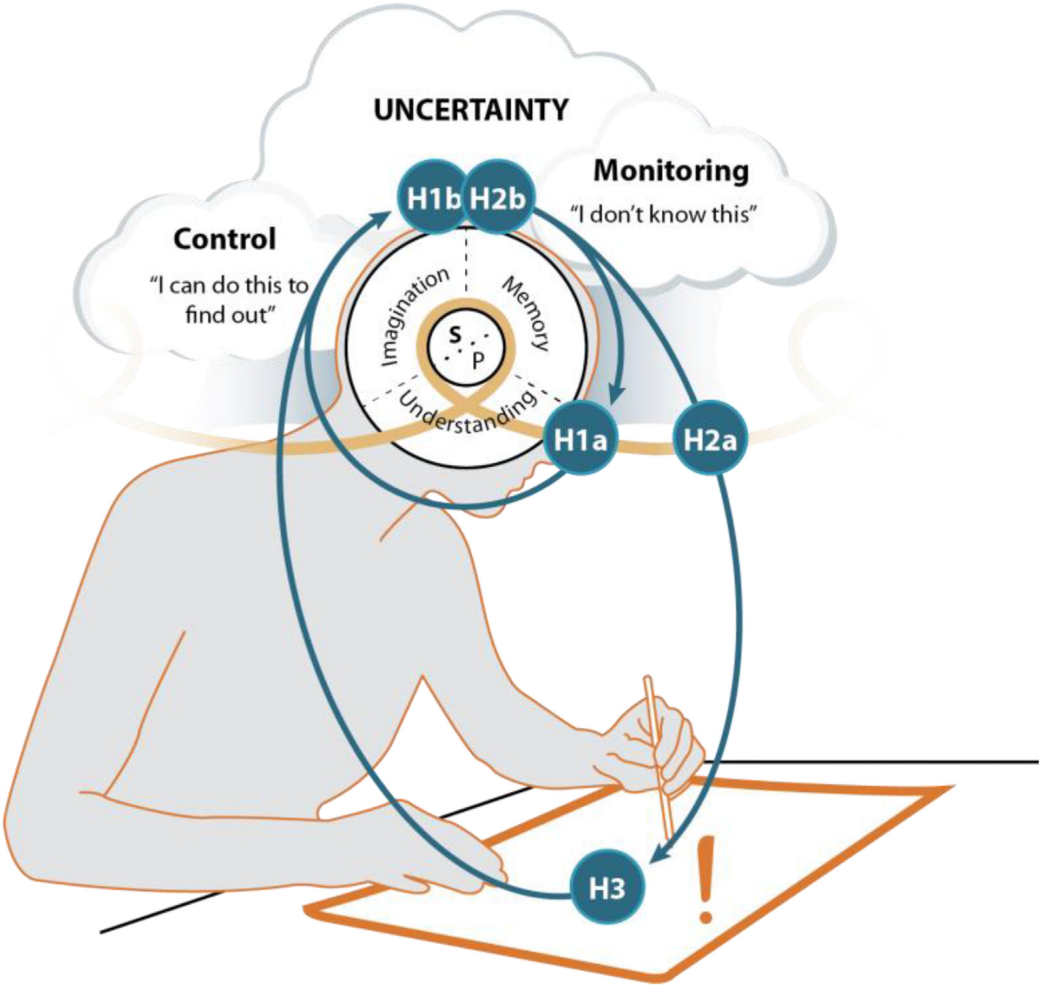


Figure 2 The hypotheses used in this study to assess the internal coherence and validity of the proposed cognitive co-evolution model

evolutionary transition should be able to be differentiated in terms of metacognitive perceived uncertainty (Cash & Kreye, 2018; Christensen & Ball, 2018). This leads us to Hypothesis 1a.

H1a: Differences in a designer's perceived uncertainty correlate with differences in types of co-evolutionary transition (P−P, P−S, S−P, and S−S).

Elaborating on this relationship, designers also act via metacognitive *control* of their own knowledge and cognition, by going through cycles of reflection and action, either implicitly or explicitly (Ackerman & Thompson, 2017; Ball & Christensen, 2019). Following the logic of H1a, co-evolutionary progression is characterized by movement from one co-evolutionary transition to another (e.g., from P−P to a new P−P, or from P−P to S−S or S−P to

P−S or any other combination). Thus, movement between transitions should be driven by differences in metacognitive perceived uncertainty (Cash & Kreye, 2018; Christensen & Ball, 2018). This leads us to Hypothesis 1b.

H1b: Differences in perceived uncertainty predict change from one type of co-evolutionary transition to another (P−P, P−S, S−P, and S−S).

Second, if designers act based on metacognitive monitoring and control correlated with the basic unit of co-evolutionary transitions, as in H1, this should also form the basis for the designers' understanding of design outputs (e.g., externalized representations of ideas, such as sketches) (Cash & Maier, 2021; Scaife & Rogers, 1996). Following the split between H1a and H1b this again has two main components, differentiating periods where design outputs are created and predicting their creation. For the purposes of testing and linking to the wider literature on co-evolution and creativity, we focus specifically on idea outputs in this work. More specifically, on the generation of a specific sketch or notation identified as an idea by the designer. Thus, periods when idea outputs are created should be able to be differentiated in terms of metacognitive perceived uncertainty and co-evolutionary transitions, because the externalisation of idea outputs triggers reflection (Self & Pei, 2014; Yang, Brik, de Jong, & Gonçalves, 2019). This leads us to Hypotheses 2a and 2b.

H2a: Differences in perceived uncertainty and co-evolutionary transitions (P−P, P−S, S−P, and S−S) correlate with periods where idea outputs are created.

H2b: Differences in perceived uncertainty and co-evolutionary transitions (P−P, P−S, S−P, and S−S) predict periods where idea outputs are created.

Taking a first step beyond the internal validity of the model for explaining moment-by-moment progression of co-evolutionary design to consider the wider design process, metacognitive monitoring and control should relate to not only the creation of outputs but also their criticality, i.e., their influence on the design process as a whole. Here, a close link has been described between representations and changes in understanding, such as realizing an alternative perspective (Gerber & Carroll, 2012; Scrivener et al., 2000) or reframing of problem or solution (Self & Pei, 2014; Yang, Brik, de Jong, & Guerreiro Goncalves, 2019). Moreover, idea outputs can have a significant non-linear impact across a whole design session, with some ideas, consciously or unconsciously, influencing others in an interconnected manner, becoming critical to the designer, i.e., linking to many other ideas (Gonçalves & Cash, 2021). In this work, relative criticality denotes the extent to which an output impacts a designer's understanding and the generation of subsequent idea outputs, following the recent work by Gonçalves and Cash (2021). Thus, while there are several steps in this logic, we tentatively propose that the criticality of idea outputs should be able to be differentiated in terms of metacognitive perceived uncertainty. This leads us to Hypothesis 3.

H3: Differences in perceived uncertainty and co-evolutionary transitions (P−P, P−S, S−P, and S−S) predict differences in the relative criticality of idea outputs.

The model (Figure 1-E) and hypotheses (Figure 2) in Sections 1 and 2 form the foundation for our empirical work and analysis.

3 Research method

To test these hypotheses, we adopted a quantitative protocol analysis-based approach. To provide a robust foundation for this, we reanalysed transcripts from the ideation study conducted by Gonçalves, Cardoso, and Badke-Schaub (2016). We outline the considerations behind this choice and summarise the relevant study information below.

3.1 Sample and data considerations

We identified the current dataset based on the sampling considerations described by Cash, Isaksson, Maier, and Summers (2022). First, by using a previously analysed sample, we mitigate possible ethical concerns and increase the transparency of the research. Second, as the proposed model is novel it is necessary to first establish the basic coherence and validity of its internal structure before taking any insights 'into the wild' (hence we consider Hypotheses 1 and 2 central and Hypothesis 3 more speculative at this stage) (Ball & Christensen, 2018; Cash, 2018). A previously published sample is ideal for this aim because it has already been peer reviewed and is available to the research community. Third, while the hypotheses are motivated in theory related to the progression of the design process, there is little current theory regarding how this might vary across the wider population of designers or possible design contexts. As such, we prioritise robust testing within a limited scope to maximise internal coherence of the dataset (Onwuegbuzie & Leech, 2007; Robson & McCartan, 2011). Here, the constrained scope of the sample and context reported by Gonçalves et al. (2016) (2021) makes this an appropriate candidate for reanalysis, and particularly suitable for our central hypotheses (1 and 2). Fourth, we differentiate the generalisability and abstraction criteria for our sample (Wacker, 2008). Specifically, we aim for internal statistical validity within the sample group to establish the model's basic robustness but aim for analytical generalisation through the abstraction of theoretical insights embodied in the model itself (Robson & McCartan, 2011, p. 154). Given these considerations, we necessarily adopt a purposive sampling schema (Onwuegbuzie & Leech, 2007). Specifically, we require a homogenous sample to maximise internal coherence and minimise possible contextual variables that might disguise relationships within the proposed model. Correspondingly, the major theoretical sampling criteria were similarity in background of the participants, level of experience, and ability to consistently follow a basic design task; as well as sufficient sample size to support internal statistical validity. Based on these criteria a student sample of between 20 and 40 is ideal (Cash et al., 2022; Onwuegbuzie & Collins, 2007). Here, Gonçalves et al. (2016) report results from 31 novice designers, which concretely establishes their relative homogeneity in their design capabilities. Thus, we selected this dataset as the basis for our analysis.

3.2 Summary of key information from Gonçalves et al.'s (2016) study

The sample was composed by 31 novice designers (Master students from an Industrial Design Engineering faculty), where 17 participants were female. The participants reported an average age of 24 and approximately 5 years of education in design, with 27 of them not having any prior professional experience.

Each designer worked individually on a design brief in sessions of 45 min. They were asked to think aloud while sketching ideas to solve the given brief. Each session was video-recorded and transcribed, where also their pen-and-paper outcomes were retrieved. This allowed the researchers to have a complete view of the designers' work and to synchronise the representation of idea outputs with verbalisation of their thinking process and behaviour. To provide a limited degree of contextual variation across the sample, participants were allocated to one of three conditions: Condition 1: no stimuli ($N = 10$), except for the given design brief; Condition 2: limited stimuli ($N = 11$), available via a search tool but with access restricted to only once during the session; and Condition 3: unlimited stimuli ($N = 10$): available via a search tool with no restrictions. The design work in each session progressed as follows:

- **Introduction of the task and warm up (5 min)**: Following a pre-questionnaire, participants were informed of the session's structure and did a warm−up activity to practice think aloud while sketching.
- **Divergence phase (30 min)**: Participants were asked to create as many different ideas as possible to answer the following brief: "Learning to sleep alone at night is a challenge for children at young age. Normally, until the age of two, parents keep their children close and have them sleep in a crib in the parents' room or even in their own bed. However, it is recommended that children make the transition to their own room and bed. Having the kids wake up during the night and come into the parents' bed is quite common and it is a big problem for parents. No one sleeps and rests conveniently, the child doesn't conquer his/her fears and parents don't have their privacy. Your task is to design a product to help children of young age (3−5 years old) sleep alone through the night, in their own bed."

- **Convergence phase (10 min)**: Participants were asked to converge, i.e., generate one final concept to answer the brief.

The progression of the design process during the 30-min divergent phase proved remarkably similar across conditions and revealed several common process structures linking representation of idea outputs to developments in the design process (Gonçalves & Cash, 2021). Moreover, the ideation task and work associated with the divergent phase is comparable to a wide swathe of prior design creativity studies (Dinar et al., 2015; Sosa, Vasconcelos, & Cardoso, 2018). Thus, the results from the 30-min divergent phase form an ideal dataset for further testing.

3.3 Operationalisation and coding of main variables

As a starting point for answering the hypotheses, three main variables were coded in the transcripts: co-evolutionary transitions; perceived uncertainty; and relative criticality of idea outputs. Here, co-evolutionary transitions also formed the basis for transcript segmentation.

3.3.1 Operationalisation and coding of co-evolutionary transitions

The traditional and well-known representation of co-evolution depicts the interaction of the problem and solution spaces following a timeline. As such, the spaces evolve via horizontal and diagonal transitions (see the initial model of co-evolution in Figure 1). Based on prior work (Becattini et al., 2015; Maher & Poon, 1996) these transitions were operationalised with respect to the expressed attention of the designer, as a proxy for 'real' transitions in knowledge, which cannot be directly observed. Thus, following Becattini et al. (2015), we coded four co-evolutionary transitions: P−P, P−S, S−P, and S−S, as described below.

P−P: A horizontal transition in the problem space, referring to problem decomposition, definition, and refinement of goals and requirements, as illustrated in Box 1.

P−S: A diagonal transition from problem to solution space, referring to the exploration of possible ideas that fit an understanding of the problem at a given moment. The start of this transition is the current problem definition, requirements, or goals, as illustrated in Box 2.

S−P: A diagonal transition from solution to problem space, referring to when ideas trigger a change or reframing of the understanding of the problem, as illustrated in Box 3.

Box 1. Example of a P—P transition: Participant 6 from Condition 3 is defining the context of the problem, i.e., the situation in which a child would not sleep alone through the night.

09:55	“okay, uhhm… safe [reading the brief and its requirements again]
10:05	“then, okay, maybe I can assume that they like to, when they get afraid, they go to their parents [bedroom]”
10:15	“and then, to get rid of the fear, like to sleep, they hold on to their parents’ hand”

Box 2. Example of a P—S transition: Participant 4 from Condition 1 starts from the problem requirement (the child needs to stay in her own bed) before exploring a possible solution to comply with the requirement (a teddy bear or night lamp).

12:36	“so maybe, and this is the parents' room…”
12:41	“hmm, there's those night light attachments, you can have there…”
12:50	“and there's a similar one in the child's room”
13:02	“they can communicate with each other”

Box 3. Example of a S—P transition: Participant 2 from Condition 2 proposes a hypothetical direction to solve the problem, leading to a reframe (rather than “sleep alone through the night”, it became “avoid fear of the dark”).

09:30	“I was thinking about the fear they have, so, and the darkness and fear are directly connected”
09:42	“so, uh, if you put the darkness away, then, yeah, the fear is gone as well, so that’s why”
09:50	“it’s the influence of the darkness”

S–S: A horizontal transition in the solution space, referring to the synthesis and elaboration of a solution (or its parts). S–S transitions start from previously created ideas, which are further refined (Box 4).

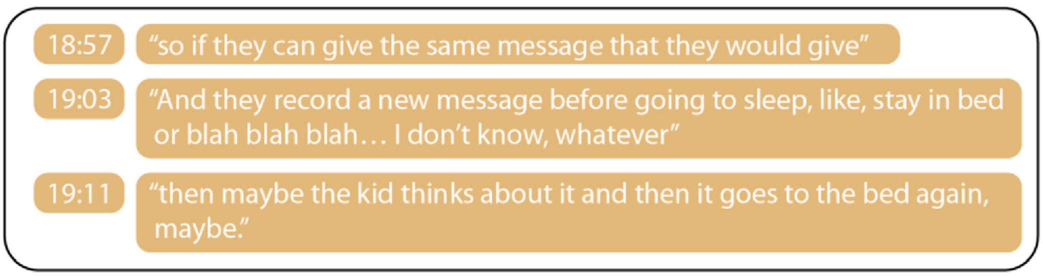
Based on this coding, co-evolutionary transitions were treated as a categorical variable with four types (reflecting the four transition types). This formed a theory-driven basis for transcript segmentation, where each segment represented one type of co-evolutionary transition, as the basic unit of the design process and our analysis. This resulted in an n of 1617 segments, comprised of circa 4 utterances per segment (where an utterance represented a participant's verbalisation of a single thought, parsed by natural pauses (e.g., Lloyd & Scott, 1994; Goldschmidt & Weil, 1998). Coding of the co-evolutionary transitions also provided a variable able to support analysis of correlations, used in H1a, H1b, and H2a.

In addition, we derived another variable from the segmentation of co-evolutionary transitions, named transition change: if consecutive segments changed their transition type, this was denoted in a binary variable. As shown in Figure 3, between Segments 1 and 2 there was no transition change (as they were both P–P transitions), while Segments 2 and 3 had a transition change. This provided a variable able to support analysis of predictions regarding progression in the design process as in H1b.

3.3.2 *Operationalisation and coding of differences in perceived uncertainty*

As metacognition cannot be directly observed we follow prior work in operationalising this with respect to verbal expressions of perceived uncertainty (Cash & Kreye, 2018; Christensen & Schunn, 2007; Wiltschnig et al., 2013). To do so, we coded perceived uncertainty in two ways, which resulted into two different but complementary variables: 1) level of perceived uncertainty and 2) change in level of perceived uncertainty.

Box 4. Example of a S–S transition: Participant 10 from Condition 1 elaborates the idea by explaining one of its functions.



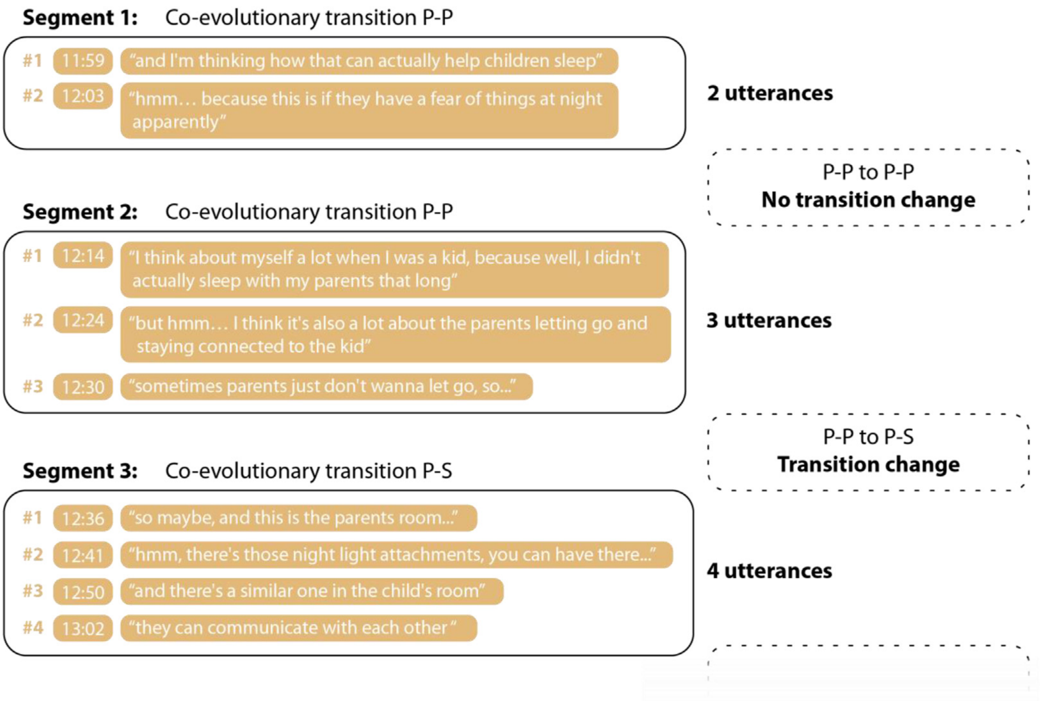


Figure 3 Internal logic of segments, utterances, and transition changes, shown in an excerpt from Participant 4, Condition 1

First, level of perceived uncertainty was coded based on a syntactical approach where 'hedge words' were used as a proxy for perceived uncertainty. The specific dictionary of words used for our analysis was drawn from Cash and Kreye (2018). Utterances containing these words were then evaluated to ensure that they reflected uncertainty in context, as illustrated in Figure 4 (orange words). This type of approach has been previously demonstrated to be highly reliable in design (Cash & Kreye, 2018; Christensen & Schunn, 2007; Wiltschnig et al., 2013).

Following the work of Christensen and Ball (2016), level of perceived uncertainty could be treated as a count or ordinal variable—depending on the statistical test—based on the number of words in each segment. This could be evaluated across the whole dataset as there were no significant differences in average level between participants. Because this data was reasonably symmetric, categories were established using the mean (= 2.88 words) ± .25 standard deviations (= 3.39)): high >4 "hedge" words; mid = 2 to 4 (inclusive); low <2. This formed the basis for evaluating differences regarding a designer's perceived uncertainty, for example in relation to co-evolutionary transitions as posited in H1a.

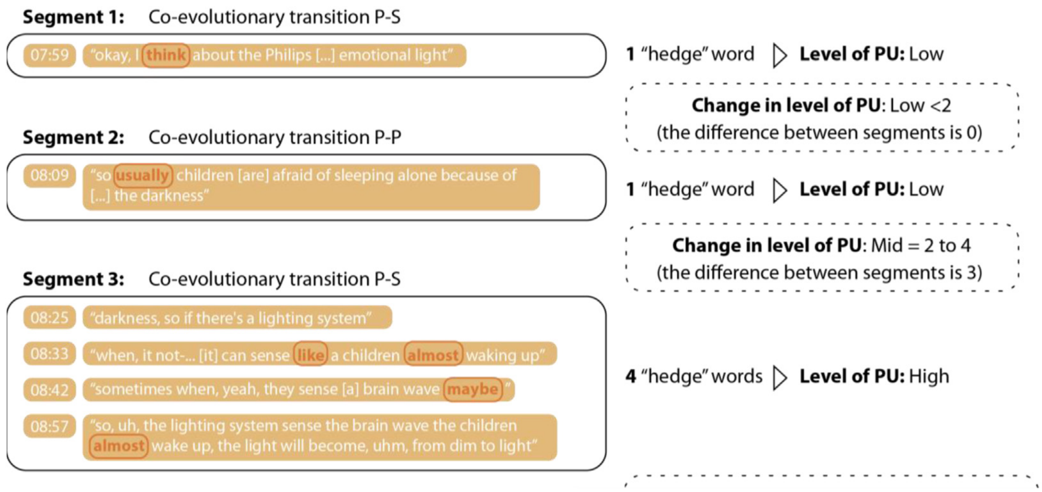


Figure 4 Internal logic of 1) level of perceived uncertainty (PU) (i.e., amount of "hedge" words in each segment) and 2) change in level of perceived uncertainty (differences between segments) illustrated in an excerpt from Participant 3, Condition 2

Second, change in level of perceived uncertainty was coded based on differences in uncertainty perception between current and prior segments, which could again be treated as a count or ordinal variable. Importantly while the counted value for change could be positive or negative (reflecting increasing or decreasing level of perceived uncertainty), the ordinal set was calculated using absolute values. Following the same procedure as level of perceived uncertainty (mean = 3.10, SD = 3.39) resulted in three categories: high >4 words; mid = 2 to 4 (inclusive); low <2. For instance, as illustrated in Figure 4, if a segment included one "hedge" word, while the following segment had four, then it was coded as having a mid-change in level of perceived uncertainty, as it had a difference of 3 words, following the categories above. This formed a secondary means for evaluating differences regarding a designer's perceived uncertainty and was used in the same way as level of perceived uncertainty. Throughout the results we denote using the *ordinal* versus *counted* variable for each test.

3.3.3 Operationalisation and coding of idea outputs and their relative criticality

Based on the creative nature of the design task, the creation of idea outputs was operationalised with respect to sketches and notes corresponding to the generation of ideas (resulting in an n of 368 idea outputs across the 31 participants). Idea occurrence was coded based on the start of an idea within a segment, which was concluded when the designer started another one, following the approach reported by Gonçalves and Cash (2021). Following prior definitions (Dean, Hender, Rodgers, & Santanen, 2006; Shah, Smith, & Vargas-Hernandez, 2003), we only considered idea occurrences that expressed a purpose and function to the brief in question, and were externalised (with sketches, notes, or a combination of both). Based on this coding, the occurrence of an idea output was treated as a binary variable.

In addition to this, the relative criticality of outputs was operationalised with respect to their influence on the wider design process (following Gonçalves & Cash, 2021, where ideas with many links, e.g., being influenced by or influencing others, are considered more critical). This was coded using network analysis (similar to Linkography (Goldschmidt, 1990)), where ideas were connected by implicit (inferred from behaviour, speech, and idea output) or explicit links (when participants explicitly referred to a connection between ideas), following similar works in this area (Cai, Do, & Zimring, 2010; Cash & Storga, 2015; Kan & Gero, 2008). Based on the number of links between ideas, their impact on the network could be evaluated, as described in Gonçalves and Cash (2021).

The relative criticality of an idea output could again be treated as a count or ordinal variable. To account for differences between participants, the links for each idea were first normalised against the total number of links in the associated participant's network. This was required because criticality was determined by links to other ideas, hence without normalisation it would not be possible to compare participants with different numbers of ideas. Because this data was skewed (with many segments containing no ideas and thus no links), categories were established using the median (= .07 normalised links) $\pm$ .25 interquartile range (IQR = .06)): high criticality >.08 links; mid = .05 to .08 (inclusive); low <.05. This provided a variable able to support analysis of predictions regarding differences in the relative criticality of idea outputs as proposed in H3.

3.4 Evaluating reliability and robustness

We evaluated four main aspects of reliability and robustness. First, intercoder reliability for the co-evolutionary transitions was analysed by the 2nd author and a research assistant (who was blind to the hypotheses to avoid potential bias). This was done in two iterative steps. A Krippendorff's alpha (Krippendorff, 2004) of .57 was achieved based on the initial data coding. As this was lower than the .667 bound (Krippendorff, 2004, p. 241), the two raters iterated on the coding, involving clarification of disagreements. Following this, an alpha of .764 was achieved, exceeding the boundary value (Krippendorff, 2004, p. 241). Thus, intercoder reliability was considered acceptable. Intercoder reliability assessment was not relevant for the other variables as these were based on a predefined dictionary (uncertainty perception) or an already defined coding (idea outputs − where 100% agreement was reached as described in the work of Gonçalves and Cash (2021, p. 10)).

Second, to ensure the robustness of our transcript segmentation (Section 3.3.2), we also coded the data and carried out analyses based on two alternative segmentations: i) single utterance segmentation, like that used by Christensen and Schunn (2009), and 10 utterance segmentation, like that that used by Chan, Paletz, and Schunn (2012). While these alternative segmentations did provide differing levels of significance in the statistical analysis, there were no substantial differences in the trend in the answers to the hypotheses. Further, these segmentations have no grounding in theory. As such, while these results are available from the authors upon request, we do not further elaborate them here in order to avoid conceptual confusion. Thus, the theory-based segmentation employed here was considered acceptable.

Third, following Paletz, Chan, and Schunn (2017), we checked that differences across participants and conditions did not introduce confounding levels of variance (in particular, requiring multilevel analysis). We found no statistically significant interactions between participants or the three conditions and the main variables (evaluated via a chi-square test of independence and as a control variable in the regression models). Thus, our aggregation of the dataset — across participants and conditions — was considered acceptable, and multilevel analysis was not considered necessary.

Fourth, where we report regression analyses including multiple variables, single variable models were also tested in all cases. Further, we generally applied stepwise regression with a standard inclusion threshold of $p < .2$ to ensure the explanatory power and robustness of the final reported model. In all cases where the final model was significant, the single variable models were also significant but had significantly lower explanatory power. This provides a high degree of confidence in the combinatory models used in Section 4.

4 *Evidencing cognitive co-evolution: results and analysis*

This section provides evidence to support our three major hypotheses related to i) the progression of the co-evolutionary process itself (H1a and b); ii) the creation of idea outputs (H2a and b); and the criticality of those idea outputs (H3).

4.1 *Relating perceived uncertainty and co-evolutionary transitions*

For H1a (*differences in a designer's perceived uncertainty correlate with differences in types of co-evolutionary transition*), we found that differences in perceived uncertainty (both in terms of *level* and *change* between segments) could differentiate types of co-evolutionary transition (P—P, P—S, S—P, and S—S). Following Gero and Tang (2001), this was evaluated via two chi-square tests of independence. Here, the relation between ordinal level of perceived uncertainty and co-evolutionary transitions was significant, X^2 (6,

$N = 1617) = 180.1$, $p < .001$, as was the relation between ordinal change in level of perceived uncertainty and co-evolutionary transitions, X^2 (6, $N = 1617) = 30.0$, $p < .001$. These results provide robust support for H1a, meaning that participants' uncertainty was related to co-evolutionary transitions. As such, it is possible to conclude that there is a relationship between the main elements in our model (perceived uncertainty and co-evolutionary transitions), logically following from the theoretical discussion in Section 2.

For H1b (*differences in perceived uncertainty predict change from one type of co-evolutionary transition to another*) we found that differences in perceived uncertainty predicted movement in the co-evolutionary process. We tested this hypothesis at three, incrementally increasing, levels of detail. First, as in H1a, we used two chi-square tests of independence. Here the relation between change in type of co-evolutionary transition and ordinal level of perceived uncertainty was significant, X^2 (2, $N = 1617) = 15.4$, $p = .001$, as was the relation with ordinal change in level of perceived uncertainty, X^2 (2, $N = 1617) = 23.9$, $p < .001$. Second, following Christensen and Schunn (2009), we used t-tests to evaluate if the level of perceived uncertainty (number of 'hedge' words per segment, as shown in Figure 4) and the change in level of perceived uncertainty (difference between segments over time, Figure 4) were different in segments where there was a change in co-evolutionary transition, compared to the base rate. Here two-sample Welch's t-tests revealed a statistically significant difference for counted level of perceived uncertainty ($t = -3.905$, $p < .001$) but not for counted change in level of perceived uncertainty ($t = -1.568$, $p = .1174$). Third, following Chan et al. (2012) and Christensen and Ball (2016), a stepwise logit regression was used to ascertain the effects of counted level of perceived uncertainty and counted change in level of perceived uncertainty on the likelihood of changes in co-evolutionary transitions. The model was significant as was level of perceived uncertainty, as outlined in Table 1. These results (chi-square, t-test, logit regression), both individually and as a whole, provide robust support for H1b. As such, it is possible to conclude that perceived uncertainty predicts a change in co-evolutionary transition type, which makes both logical and theoretical sense, with uncertainty being the driver for action. This indicates that, as levels of uncertainty change, so do designers explore different parts of the problem and solution spaces.

Based on the support for H1a and H1b, we conclude that there is evidence for metacognitive monitoring and control of the co-evolutionary design process. These results demonstrate the descriptive and explanatory power of our proposed cognitive co-evolution model (Figure 1-E), as illustrated in Figure 5. Notable in Figure 5 A) is that each type of co-evolutionary transition shows significantly different perceived uncertainty, either in level or change in level or both. Similarly, Figure 5 B) shows the significantly higher level and change in perceived uncertainty when there is a change in type of co-evolutionary transition. As such, the cognitive co-evolution model can not only distinguish

Table 1 Results of logit regression for changes in co-evolutionary transitions

Logit regression						Number of obs.	1617
						LR $X^2(2)$	16.11
						Prob. > X^2	.0003
						Pseudo R^2	.0101
						Log likelihood	−790.7
Change in co-evolutionary transitions	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**		
Level of perceived uncertainty	.1050	.0292	3.60	.000	.0478		.1621
Change in level of perceived uncertainty	−.0289	.0201	−1.44	.151	−.0684		.0106
Constants	1.1397	.0956	11.92	.000	.9523		1.3271

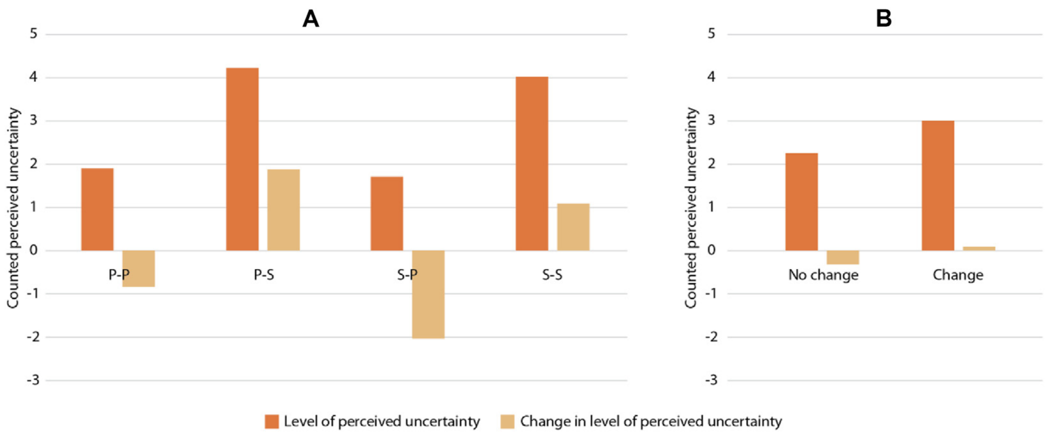


Figure 5 Illustration of how differences in perceived uncertainty differentiate A) co-evolutionary transitions and B) change in co-evolutionary transitions (negative perceived uncertainty indicates expression of certainty)

different transitions in the co-evolution process but also the progression between these transitions, driven by perceived uncertainty. We can understand when designers are going to explore a different perspective of the problem and solution, as it coincides with a change in how (un)certain they are. Uncertainty perception thus provides a common means for understanding both the design process and its progress. Not only does this confirm theoretical assumptions (Ackerman & Thompson, 2017; Ball & Christensen, 2019), but also aligns with expectations drawn from prior research on uncertainty driven action in design (Cash & Kreye, 2018; Christensen & Ball, 2018).

4.2 Relating perceived uncertainty and idea outputs

Given the support for H1a and H1b, it is logical to test the wider predictive power of the cognitive co-evolution model as in H2a (*differences in perceived uncertainty and co-evolutionary transitions correlate with periods where idea outputs are created*). Following the same multi-level analytical process as in H1a, we found that differences in perceived uncertainty and co-evolutionary transition clearly differentiate periods where idea outputs are created. First, the relation between the creation of an idea output and ordinal level of perceived uncertainty was significant, X^2 (2, $N = 1617$) = 200.6, $p < .001$, as was the relation with ordinal change in level of perceived uncertainty, X^2 (2, $N = 1617$) = 65.3, $p < .001$, and co-evolutionary transitions, X^2 (3, $N = 1617$) = 382.8.4, $p < .001$. Second, for periods with idea outputs, two-sample Welch's t-tests revealed a significant difference in counted level of perceived uncertainty ($t = -12.174$, $p < .001$) and counted change in level of perceived uncertainty ($t = -10.082$, $p < .001$). Third, a stepwise logit regression was used to ascertain the effects of counted level of perceived uncertainty, counted change in level of perceived uncertainty, and co-evolutionary transitions on the likelihood of an idea output being created. The model was significant as was level of perceived uncertainty and co-evolutionary transitions, as outlined in Model 1 – Table 2. These results (individual and as a whole) provide robust support for H2a. As such, we can conclude that the creation of idea outputs correlates with distinctive developments in the cognitive co-evolution process. This aligns with theoretical expectations of idea outputs acting as

Table 2 Results of logit regression for idea outputs being created at t and $t+1$

Model 1: Logit regression						
					Number of obs.	1617
					LR $X^2(2)$	228.75
					Prob. > X^2	.0000
					Pseudo R^2	.1319
					Log likelihood	−752.9
Idea output created	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	
Level of perceived uncertainty	.2351	.0272	8.66	.000	.1819	.2883
Change in level of perceived uncertainty	.0351	.0201	1.74	.081	−.0043	.0746
Co-evolutionary transitions	−.2258	.0705	−3.20	.001	−.3641	−.0876
Constants	−1.5636	.1641	−9.52	.000	−1.8854	−1.2419
Model 2: Logit time lagged regression					Number of obs.	1585
					LR $X^2(2)$	35.79
					Prob. > X^2	.0000
					Pseudo R^2	.0213
					Log likelihood	−822.7
Idea output created	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	
Lag 1 Level of perceived uncertainty	.0377	.0241	1.57	.117	−.0094	−.0849
Lag 1 Change in level of perceived uncertainty	−.0429	.0169	−2.54	.011	−.0760	−.0098
Lag 1 Co-evolutionary transitions	−.3681	.0683	−5.39	.000	−.5020	−.2343
Constants	−.6401	.1505	−4.25	.000	−.9350	−.3452

critical externalisations of understanding that anchor progression of creative processes (Self & Pei, 2014; Yang et al., 2019).

Continuing this logic to H2b (*differences in perceived uncertainty and co-evolutionary transitions predict periods where idea outputs are created*) a time-lagged analysis was used. A stepwise logit regression was performed to ascertain the effects of counted level of perceived uncertainty, counted change in level of perceived uncertainty, and co-evolutionary transitions at time *t*, on the likelihood of an idea output being created at *t*+1. The model was significant as was change in level of perceived uncertainty and co-evolutionary transitions, as outlined in Model 2 − Table 2. Coupled with the prior results, this provides support for H2b. As such, we can anticipate when idea outputs will be created based on developments in the cognitive co-evolution process. This again corresponds to the basic theoretical assumption that uncertainty perception drives design processes, and that idea outputs act as externalisations and concretise understanding in a way that directly interacts with uncertainty perception via representation-based reflection (Cash & Maier, 2021; Scaife & Rogers, 1996).

Finally, given the support for H2a and H2b we analysed the more limited dataset associated with the created idea outputs themselves (n = 368) for H3 (*differences in perceived uncertainty and co-evolutionary transitions predict differences in the relative criticality of idea outputs*). Using chi-square tests of independence, we first found that the relation between ordinal relative criticality of idea outputs and ordinal level of perceived uncertainty was significant, X^2 (4, $N = 368$) = 11.2, $p = .024$. On the other hand, the relation with ordinal change in level of perceived uncertainty was not, X^2 (4, $N = 368$) = 7.5, $p = .109$, as was the relation with co-evolutionary transitions, X^2 (6, $N = 368$) = 10.36, $p = .110$. Further, an ordered logit regression for counted level of perceived uncertainty and counted change in level of perceived uncertainty was significant at time t (Model 1 −Table 3) but not at *t*+1 (Model 2 − Table 3). Together, these results provide support for H3, which indicates that, not only can perceived uncertainty and co-evolutionary transitions signal when ideas outputs will be created, but also how critical those ideas are for the overall design process. As with the above results, this helps strengthen the idea that uncertainty perception acts as a driver for design work and has strong interactions with all the major elements of co-evolutionary design, including both the process and its outputs. However, it is clear that further work is needed to explore the wider external predictive power of the model, as well as how patterns of uncertainty perception might develop over time or how certain patterns might predict specific developments in the process or characteristics of design outputs.

Based on the support for H2a, H2b, and H3, we conclude that there is evidence for metacognitive monitoring and control of co-evolutionary creation of idea

Table 3 Results of ordered logit regression for relative criticality of idea outputs at t and $t+1$

Model 1: Ologit regression					Number of obs.	368
					LR $X^2(2)$	14.35
					Prob. > X^2	.0025
					Pseudo R^2	.0181
					Log likelihood	−390.2
Relative criticality of idea outputs	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	
Level of perceived uncertainty	.0922	.0353	2.61	.009	.0230	.1613
Change in level of perceived uncertainty	−.0254	.0278	−.92	.360	−.0799	.0290
Co-evolutionary transitions	.1885	.1569	1.20	.230	−.1191	.4960
Model 2: Ologit time lagged regression					Number of obs.	368
					LR $X^2(2)$	4.12
					Prob. > X^2	.2485
					Pseudo R^2	.0054
					Log likelihood	379.4
Relative criticality of idea outputs	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	
Lag 1 Level of perceived uncertainty	.0761	.0396	1.92	.055	−.0015	.1536
Lag 1 Change in level of perceived uncertainty	−.0485	.0275	−1.76	.078	−.1024	.0054
Lag 1 Co-evolutionary transitions	−.0216	.1041	−.21	.836	−.2257	.1824

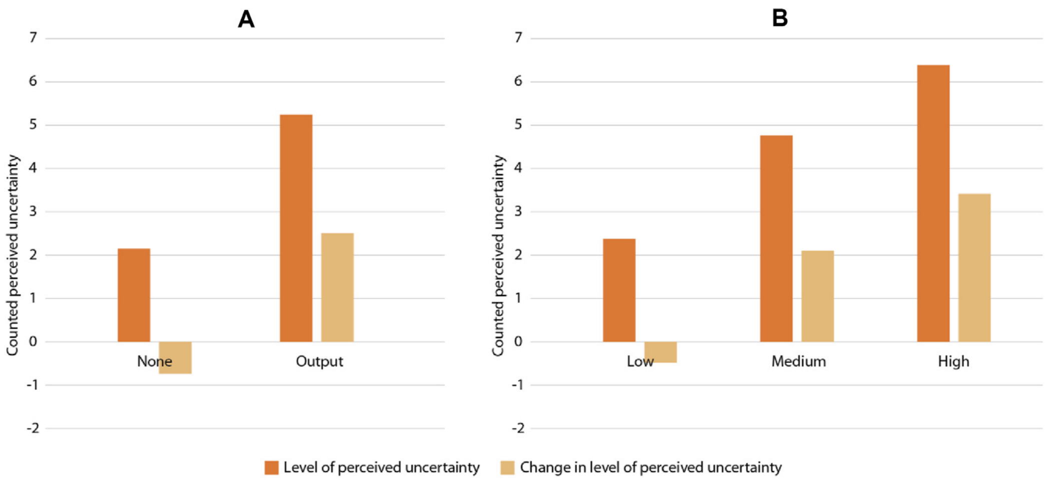


Figure 6 Illustration of how differences in perceived uncertainty differentiate A) periods where an idea output is created and B) the ordinal relative criticality of the idea output

outputs of varying degrees of criticality. These results demonstrate the descriptive, explanatory, and predictive power of our proposed cognitive co-evolution model (Figure 1-E), as illustrated in Figure 6. Notable in Figure 6 A) is that there is significantly higher level and change in perceived uncertainty in periods where an idea output is created. Similarly, Figure 6 B) illustrates the significant differences in level and change in perceived uncertainty between idea outputs with low, medium, and high criticality. These results support the proposition that uncertainty perception interacts with idea outputs (Gerber & Carroll, 2012; Scrivener et al., 2000) as well as the more general progression of the design process (Cash & Kreye, 2018; Christensen & Ball, 2018). This brings together prior theoretical discussions of the relationships between progression of the design process, design cognition, and design representations via the common lens of uncertainty perception and situated behaviour and cognition, as outlined in Section 2.

4.3 Limitations and future directions

There are two main limitations to highlight prior to discussing the implications of these results. First, in terms of theorising, we deliberately limit the scope of our discussion at this juncture to individual design cognition and co-evolutionary processes. This followed the original approach to co-evolution and allowed us to elaborate the theory without being overwhelmed by complexity (Wacker, 2008). However, it also points to the need for future work to examine how these processes and mechanisms play out and can be explained in the team context. This introduces several additional considerations, such as affect and shared states (Grossman, Friedman, & Kalra, 2017), as well as significantly complicating the explanation of any given design process. Yet, it is the logical next step for further development of co-evolutionary theory and integration of individual and team discussions in the design literature more generally.

Second, in terms of empirical work, we have employed a student sample coupled with a lab-based setting and task. This allowed us to maximise the internal validity of our study and focus on testing the internal coherence and validity of the proposed model itself (Cash et al., 2022). However, it also introduces the need for future work to expand the scope of testing to expert designers in a constrained context and ultimately to unconstrained design work with a varied sample of practicing designers 'in the wild' (Ball & Christensen, 2018). Such an expansion would increase confidence in the proposed model and address external validity considerations but would also significantly increase the complexity of data and make isolation of core mechanisms more difficult. Similarly, the reported relationships could be further explored to examine if there are characteristic patterns of uncertainty related to the different types of co-evolutionary transition or even to different types of ideas in different settings; with such insights being able to expand the scope and sample of testing to draw out such patterns. As such, this empirical expansion should be carried out incrementally, building on the internal validity provided by the foundational results reported in this work.

5 Discussion and implications

This research aimed to more closely connect description of what designers do to explanation of how designers think, by overcoming four key challenges facing co-evolutionary design theory: *scale*, *context*, *direction*, and *emergence*. We have taken a step toward this aim by proposing and testing the cognitive co-evolution model. Integrating design description and cognitive explanation in this model allowed us to trace co-evolution in design and show how it is directed, and how design ideas emerge, via an interplay between metacognitive perceived uncertainty, cognition, and the external world (Figure 7). This forms the basis for explaining and predicting both the progression of the co-evolutionary process itself and the creation of design outputs (specifically the creation of idea outputs in our study). The model progresses our knowledge from the general notion that co-evolution happens in design to specific detailed cognitive mechanisms and design behaviour. This strengthens both the cognitive understanding of design and the way its underlying logic plays

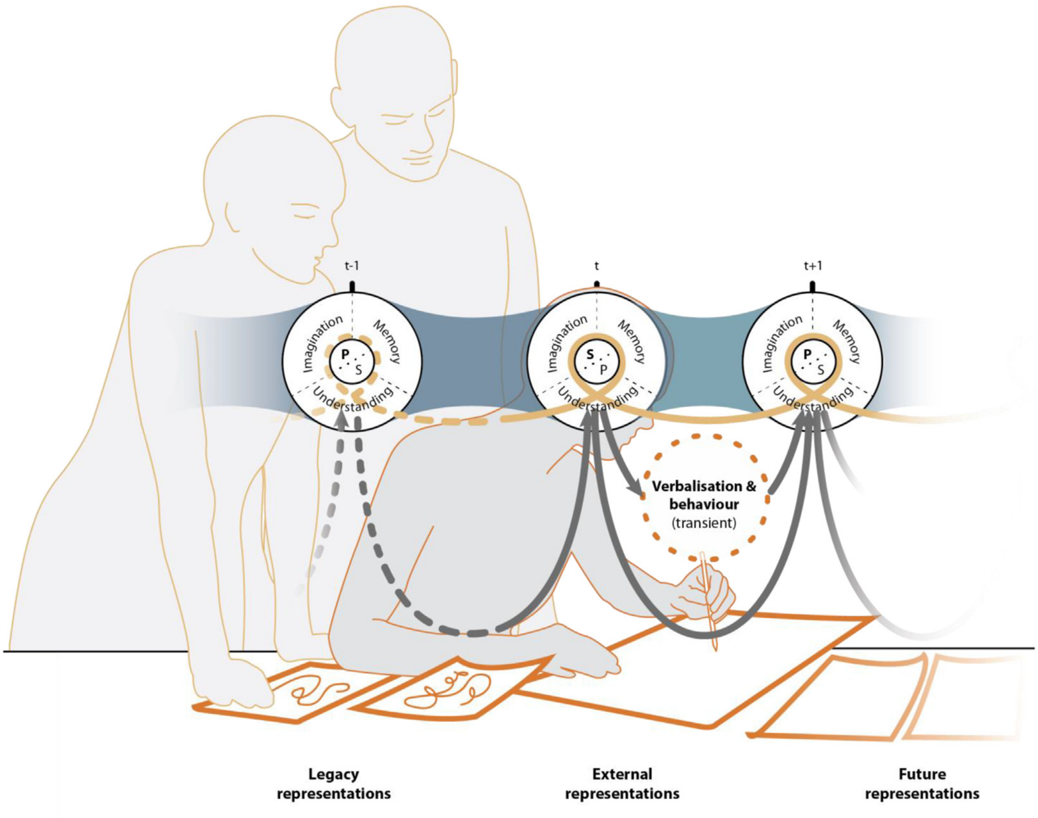


Figure 7 The cognitive co-evolution model illustrated in context. Note how the model situates co-evolution within an understanding of the design process in time as well as with respect to the external world (e.g., in design collaborations), and paves the way to more complex theorising of interactions between individual and group scale co-evolution

out in practice. The development of the model and its elements are detailed in Figure 1, while Figure 7 illustrates the model in the context of design work, as a basis for future research. Here, each individual will have their own cognitive co-evolutionary process, as well as there being an emergent and shared team-level co-evolutionary process with individuals connected via exchange of verbalisation, behaviour, and representation. As such, scaling co-evolutionary understanding beyond the individual introduces non-trivial additional complexity requiring further study.

The focused, detailed explanation offered by the cognitive co-evolution model forms a basis for connecting to other theories, models, and questions in design research via common links to cognition and metacognition. What can we learn, in terms of the relationship between co-evolution and the theories and models on design emergence, nested design processes, and practices around creative iteration (what is a 'good' iteration) in design?

First, our model builds on metacognitively directed knowledge progression as a basic unit of the cognitive co-evolution process. This changes the perspective on co-evolutionary episodes from static, discreetly segmented states to fundamental, dynamic, and relative design actions related to the perceived uncertainty of the designer. These can be aggregated at different levels to shape overall design processes (Bedny & Harris, 2005; Cash & Kreye, 2017), whilst still retaining the fundamental interaction between problem and solution found across scales in the design literature (Gero, Kannengiesser, & Crilly, 2022). As such, the integration of perceived uncertainty as a driver of the co-evolutionary process allows us to start to ask questions like: 'can design emergence be understood in terms of the (gradual) reduction (or variation) of perceived uncertainty?'; because for each co-evolutionary transition the designer goes through a reflective, metacognitive loop (Figures 2 and 7). Further, by connecting internal cognitive processes to emergent design representations and insights, the proposed model has the potential to be expanded in relation to team processes. Here, emergent states vary as a function of process progression and form both inputs for and proximal outcomes of processes (Marks, Mathieu, & Zaccaro, 2001). Therefore, parallels can be drawn to design frames, solution ideas, or representations as states that emerge from the design process. Hence, it provides a potential foundation for connecting design cognition (as addressed in this paper), with ideas of emergence in design (Dorst, 2019) and design team processes (Dong, 2005; Grossman et al., 2017). Thus, it is possible to dissolve the tension between descriptions of gradually developing co-evolutionary understanding and uncertainty reduction (Crilly & Moroşanu Firth, 2019; Dorst, 2019) with those of sudden insight and complex linkages to past ideas, with dynamic variation in uncertainty (Cai et al., 2010; Gonçalves & Cash, 2021). This allows us to continue exploring a multitude of questions, such as, can this be useful in understanding when emergence might occur, how it might lead a designer astray by pointing to only a local optimum, and how it might connect individual and team design processes?

Second, responding to the challenge of scale, we have concentrated on the cognitive process of co-evolution. However, co-evolutionary descriptions in design reflect nested 'levels' (e.g., with moment-by-moment individual development nested within task-by-task project level development) (Gero et al., 2022). While this points to key areas of understanding for co-evolution, including the development of shared co-evolutionary models in teams, it also highlights questions surrounding how this might be explained in parallel with descriptions at the project scale. For example, co-evolution can also happen across generations of products, with each new generation reacting to the one before, pulling the lessons drawn from that solution back into the problem space. While such nesting could be thought of in terms of its effects on the wider understanding and perceived uncertainty of individual designers (as in our model), it also highlights the need to better understand how such individual insights might be shared and developed within a team and organisation across levels. Further, this nested structure also significantly expands the scope of influences on co-evolution to include social and team processes, such as interpersonal affect and organisational mindset, which can substantially influence the cognition and behaviour of individuals. As such, the question here is how insights from detailed, cognitive understanding of co-evolution can be transferred to and interact with other, higher levels of co-evolution.

Finally, the key position of perceived uncertainty within the cognitive co-evolution model invites questions about what this actually means for the designer in practice, and how its impact can be related to the varied descriptions of creativity found in the literature. This links co-evolution to wider understanding of, for example, creativity in the face of uncertainty or constraint (Beghetto, 2021; Onarheim & Biskjaer, 2017), and connects to other aspects of knowledge that might co-evolve, such as the 'business space' as described by Crilly and Moroşanu Firth (2019). Here, perceived uncertainty forms a common driver for several theoretical discussions (Cash & Kreye, 2017), and is a key differentiating factor in an array of domains (MacCormack & Verganti, 2003; O'Connor & Rice, 2013). It seems that individual perceived uncertainty goes up and down wildly during a design process (while we expect overall uncertainty (and its perception) to go down more steadily, as design exploration yields more knowledge). In design practice, uncertainty is often mentioned implicitly, using words like: 'seeking closure', 'opening up', 'giving up' (abandoning a line of exploration that earlier looked promising), or the assessment of 'fruitfulness'. These each reflect different aspects of reflective metacognitive monitoring and control and thus hint at the breadth and complexity of perceived uncertainty effects in design. Hence, the question is in what way this dynamic perceived uncertainty is a driver for wider creativity and decision-making, how its changing character and level might affect these, and how its reduction (within or across scales) might relate to successful (or unsuccessful) design outcomes.

6 Conclusions

Even detailed descriptions of co-evolutionary behaviour can disguise the underlying cognitive processes of a designer. This creates a disconnect between foundational explanations (based on designer's thinking) and descriptions of design (based on designers' actions and emergent problem and solution propositions). In this paper, we take a step toward addressing this disconnect by overcoming four key challenges facing co-evolutionary design theory: *scale*, *context*, *direction*, and *emergence*. We do this by proposing and testing the *cognitive co-evolution model* (Figure 1). This explains both the progression of the co-evolutionary process itself and the creation of design outputs via an interplay between metacognitive perceived uncertainty, cognition, and the external world. Our results strongly support the proposed model and firmly close the door on apparent trial-and-error descriptions of co-evolution. We explain how designers navigate the complexities and unknowns in their problem situations to arrive at a possible understanding of the problem and solution, illuminating a subtle and thoughtful navigation process at the core of design practice.

The cognitive co-evolution model not only extends discussions of co-evolution, but also forms a basis for connecting to other theories, models, and questions in design research by creating common links to cognition and metacognition. However, our empirical work has focused on testing the internal coherence and validity of the proposed model itself. A key next step in this research would be studying expert designers to unearth their—potentially more complex and nuanced—patterns of co-evolution and perceived uncertainty, as well as exploring the wider interaction between individual co-evolution and other design processes happening across the scales of design 'in the wild'. Despite there is much yet to explore, the cognitive co-evolution model takes a major step toward addressing the four key challenges stymieing current co-evolutionary theory. In doing so, we connect explanations of how designers think with descriptions of how they act.

Declaration of competing interest

One of the authors of this article is part of the Editorial Board of Design Studies. To avoid potential conflicts of interest, the responsibility for the editorial and peer-review process for this article lies with the journal's other editors. Furthermore, the authors of this article were not part of the peer review process and have no access to confidential information related to the editorial process of this article.

Data availability

The data that has been used is confidential.

References

Ackerman, R., & Thompson, V. A. (2017). Meta-reasoning: Shedding metacognitive light on reasoning research. In L. J. Ball, & V. Thompson (Eds.), *The Routledge international handbook of thinking and reasoning* (pp. 1–15). UK: London: Psychology Press.

Ball, L. J., & Christensen, B. T. (2018). Designing in the wild. *Design Studies, 57*(1995), 1–8.

Ball, L. J., & Christensen, B. T. (2019). Advancing an understanding of design cognition and design metacognition: Progress and prospects. *Design Studies, 65*, 35–59.

Becattini, N., Cascini, G., & Rotini, F. (2015). OTSM-TRIZ Network of Problems for evaluating the design skills of engineering students. *Procedia engineering, 131*, 689–700.

Bedny, G. Z., & Harris, S. R. (2005). The systemic-structural theory of activity: Applications to the study of human work. *Mind, Culture and Activity, 12*(2), 128–147.

Beghetto, R. A. (2021). There is no creativity without uncertainty: Dubito Ergo Creo. *Journal of Creativity, 31*, 100005.

Cai, H., Do, E. Y. L., & Zimring, C. M. (2010). Extended linkography and distance graph in design evaluation: An empirical study of the dual effects of inspiration sources in creative design. *Design Studies, 31*(2), 146–168.

Cash, P. (2018). Developing theory-driven design research. *Design Studies, 56*, 84e119.

Cash, P., & Gonçalves, M. (2017). Information-triggered Co-evolution: A combined process perspective. In B. T. Christensen, L. J. Ball, & K. Halskov (Eds.), *Analysing design thinking: Studies of cross-cultural Co-creation* (pp. 501–520). CRC Press.

Cash, P., Isaksson, O., Maier, A., & Summers, J. D. (2022). Sampling in design research: Eight key considerations. *Design Studies, 78*, 101077.

Cash, P., & Kreye, M. E. (2017). Uncertainty driven action (UDA) model: A foundation for unifying perspectives on design activity. *Design Science, 3*(e26), 1–41.

Cash, P., & Kreye, M. E. (2018). Exploring uncertainty perception as a driver of design activity. *Design Studies, 54*(January), 50–79.

Cash, P., & Maier, A. M. (2021). Understanding representation: Contrasting gesture and sketching in design through dual-process theory. *Design Studies, 73*, 100992.

Cash, P., & Storga, M. (2015). Multifaceted assessment of ideation: Using networks to link ideation and design activity. *Journal of Engineering Design, 26*(10–12), 391–415.

Chan, J., Paletz, S. B. F., & Schunn, C. D. (2012). Analogy as a strategy for supporting complex problem solving under uncertainty. *Memory & Cognition, 40*(8), 1352–1365.

Christensen, B. T., & Ball, L. J. (2016). Creative analogy use in a heterogeneous design team: The pervasive role of background domain knowledge. *Design Studies, 46*, 38–58.

Christensen, B. T., & Ball, L. J. (2018). Fluctuating epistemic uncertainty in a design team as a metacognitive driver for creative cognitive processes. *CoDesign, 14*(2), 133−152.
Christensen, B. T., & Schunn, C. D. (2007). The relationship of analogical distance to analogical function and preinventive structure: The case of engineering design. *Memory & Cognition, 35*(1), 29−38.
Christensen, B. T., & Schunn, C. D. (2009). The role and impact of mental simulation in design. *IEEE Transactions on Engineering Management, 344*, 327−344.
Crilly, N. (2021a). The evolution of "Co-evolution" (Part I): Problem solving, problem finding, and their interaction in design and other creative practices. *She Ji: The Journal of Design, Economics, and Innovation, 7*(3), 309−332.
Crilly, N. (2021b). The Evolution of "Co-evolution" (Part II): The Biological Analogy, Different Kinds of Co-evolution, and Proposals for Conceptual Expansion. *She Ji, 7*(3), 333−355. https://doi.org/10.1016/j.sheji.2021.07.004.
Crilly, N., & Moroşanu Firth, R. (2019). Creativity and fixation in the real world: Three case studies of invention, design and innovation. *Design Studies, 64*, 169−212.
Cross, N. (1982). Designerly ways of knowing. *Design Studies, 3*(4), 221−227.
Cross, N. (1996). *The method in their madness: Understanding how designers think*. TU Delft Talk. Delft: TU Delft.
Dean, D., Hender, J., Rodgers, T., & Santanen, E. (2006). Identifying quality, novel and creative ideas: Constructs and scales for idea evaluation. *Journal of the Association for Information Systems, 7*(10), 646−699.
Dinar, M., Shah, J. J., Cagan, J., Leifer, L., Linsey, J., Smith, S. M., et al. (2015). Empirical studies of designer thinking: Past, present, and future. *Journal of Mechanical Design, 137*(2), 021101.
Dong, A. (2005). The latent semantic approach to studying design team communication. *Design Studies, 26*(5), 445−461.
Dorst, K. (2015). *Frame innovation: Create new thinking by design*. MIT Press.
Dorst, K. (2019). Co-evolution and emergence in design. *Design studies, 65*.
Dorst, K., & Cross, N. (2001). Creativity in the design process: Co-Evolution of problem-solution. *Design Studies, 22*(5), 425−437.
Evans, J. S. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology, 59*, 255−278.
Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science, 8*(3), 223−241.
Gabora, L. (2011). An analysis of the blind variation and selective retention theory of creativity. *Creativity Research Journal, 23*(2), 155−165.
Gerber, E., & Carroll, M. (2012). The psychological experience of prototyping. *Design Studies, 33*(1), 64−84.
Gero, J. S., Kannengiesser, U., & Crilly, N. (2022). Abstracting and formalising the design co-evolution model. *Design Science, 8*.
Gero, J. S., & Tang, H. H. (2001). The differences between retrospective and concurrent protocols in revealing the process-oriented aspects of the design process. *Design Studies, 22*(3), 283−295.
Goldschmidt, G. (1990). Linkography: Assessing design productivity. In *Cyberbetics and System'90, proceedings of the tenth European meeting on cybernetics and systems research* (pp. 291−298). Singapore: World Scientific.
Goldschmidt, G., & Weil, M. (1998). Contents and Structure in Design Reasoning. *Design Issues, 14*(3), 85−100.

Gonçalves, M., Cardoso, C., & Badke-Schaub, P. (2016). Inspiration choices that matter: The selection of external stimuli during ideation. *Design Science, 2*(November), e10.
Gonçalves, M., & Cash, P. (2021). The life cycle of creative ideas: Towards a dual-process theory of ideation. *Design Studies, 72*, 100988.
Gorman, J. C. (2014). Team coordination and dynamics: Two central issues. *Current Directions in Psychological Science, 23*(5), 355–360.
Grossman, R., Friedman, S., & Kalra, S. (2017). Teamwork processes and emergent states. In E. Salas, R. Rico, & J. Passmore (Eds.), *The wiley blackwell handbook of the psychology of team working and collaborative processes* (1st ed.). (pp. 245–269) John Wiley & Sons.
Kan, J. W. T., & Gero, J. S. (2008). Acquiring information from linkography in protocol studies of designing. *Design Studies, 29*(4), 315–337.
Kozlowski, S. W. J., Chao, G. T., Grand, J. A., Braun, M. T., & Kuljanin, G. (2016). Capturing the multilevel dynamics of emergence: Computational modeling, simulation, and virtual experimentation. *Organizational Psychology Review, 6*(1), 3–33.
Kreye, M. E., Goh, Y. M., Newnes, L. B., & Goodwin, P. (2012). Approaches of displaying information to assist decisions under uncertainty. *Omega - International Journal of Management Science, 40*(6), 682–692.
Krippendorff, K. (2004). Reliability in content analysis: Some common misconceptions and recommendations. *Human Communication Research, 30*(3), 411–433.
Kroll, E., & Koskela, L. (2015). On abduction in design. In *Design computing and cognition '14. DCC 2014 (V)* (pp. 327–344). London: Springer.
Lloyd, P., & Scott, P. (1994). Discovering the design problem. *Design Studies, 15*(2), 125–140.
MacCormack, A., & Verganti, R. (2003). Managing the sources of uncertainty: Matching process and context in software development. *Journal of Product Innovation Management, 20*(3), 217–232, (Journal Article).
Maher, M. L., & Poon, J. (1996). Modeling design exploration as Co-evolution. *Computer-Aided Civil and Infrastructure Engineering, 11*(3), 195–209.
Maher, M. L., & Tang, H. H. (2003). Co-evolution as a computational and cognitive model of design. *Research in Engineering Design, 14*(1), 47–64.
Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A temporally based framework and taxonomy of team processes. *Academy of Management Review, 26*(3), 356–376.
Martinec, T., Skec, S., Perisic, M. M., & Storga, M. (2020). Revisiting problem-solution Co-evolution in the context of team conceptual design activity. *Applied Sciences, 10*, e6303.
Miller, R. (Ed.). (2018). *Transforming the future*. London: Routledge.
O'Connor, G. C., & Rice, M. P. (2013). A comprehensive model of uncertainty associated with radical innovation. *Journal of Product Innovation Management, 30*(SUPPL 1), 2–18, (Journal Article).
Onarheim, B., & Biskjaer, M. M. (2017). Balancing constraints and the sweet spot as coming topics for creativity research. In L. J. Ball (Ed.), *Creativity in design: Understanding, capturing, supporting* (pp. 1–18).
Onwuegbuzie, A. J., & Collins, K. M. T. (2007). A typology of mixed methods sampling designs in social science research. *Qualitative Report, 12*(2), 281–316.
Onwuegbuzie, A. J., & Leech, N. L. (2007). Sampling designs in qualitative research: Making the sampling process more public. *Qualitative Report, 12*(2), 19–20.

Paletz, S. B. F., Chan, J., & Schunn, C. D. (2017). The dynamics of micro-conflicts and uncertainty in successful and unsuccessful design teams. *Design Studies, 50*, 39–69.
Robson, C., & McCartan, K. (2011). *Real world research* (4th ed.). Chichester: Wiley.
Roozenburg, N. F. M., & Eekels, J. (1995). *Product design: Fundamentals and methods*. Chichester: John Wiley Sons.
Scaife, M., & Rogers, Y. (1996). External cognition: How do graphical representations work? *International Journal of Human-Computer Studies, 45*(2), 185–213.
Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19*(4), 460–475.
Scrivener, S. A. R., Ball, L. J., & Tseng, W. (2000). Uncertainty and sketching behaviour. *Design Studies, 21*(5), 465–481.
Self, J., & Pei, E. (2014). Reflecting on design sketching: Implications for problem-framing and solution focused conceptual ideation. *Archives of Design Research, 27*(3), 65–87.
Shah, J. J., Smith, S. M., & Vargas-Hernandez, N. (2003). Metrics for measuring ideation effectiveness. *Design Studies, 24*(2), 111–134.
Simonton, D. K. (2010). Creative thought as blind-variation and selective-retention: Combinatorial models of exceptional creativity. *Physics of Life Reviews, 7*(2), 156–179.
Sosa, R., Vasconcelos, L. A., & Cardoso, C. C. (2018). Design briefs in creativity studies. In *The fifth international conference on design creativity (ICDC2018)* (pp. 403–410).
Wacker, J. G. (2008). A conceptual understanding of requirements for theory-building research: Guidelines for scientific theory building. *Journal of Supply Chain Management, 44*(3), 5–15.
Wiltschnig, S., Christensen, B. T., & Ball, L. J. (2013). Collaborative problem-solution co-evolution in creative design. *Design Studies, 34*(5), 515–542.
Yang, Y., Brik, N., de Jong, P., & Guerreiro Goncalves, M. (2019). Visualised frames: How sketching influences framing behaviour in design teams. In *Proceedings of the 22nd international conference on engineering design (ICED19)*. Delft, The Netherlands: Cambridge University Press.